2014 Annual Progress Report for

ASSESSMENT OF DROUGHT IMPACTS ON SELECTED FISH AND WILDLIFE SPECIES IN THE SOUTHWESTERN U.S.

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As outlined in our original proposal, this project is comprised of 4 subprojects on desert bighorn sheep, American pronghorn, Rio Grande cutthroat trout, and scaled quail. Since receiving funding in August 2013, all of the subprojects have been initiated. Following are summaries of research activities for each of the subprojects that have occurred to date.

Influence of Extreme Climatic Variability and Drought on Habitat and Forage Selection of Desert Bighorn Sheep

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Problem statement and implications: We were studying the impacts of drought on desert bighorn sheep on the Cabeza Prieta National Wildlife Refuge in southwestern Arizona from 2002-2005. This period spanned the range of variability in the climatic conditions in the Sonoran Desert from the worst drought on record for the area, through periods of average precipitation and ending during a wet period. This fortuitous timing, allowed us to collect GPS collar data from over 30 female desert bighorn sheep, data on the seasonal nutritional content of key forage plants, availability of key forage plants obtained from vegetation surveys in foraging areas, and fecal samples from which we were able to determine diet.

Goals and objectives: We are using this data to assess the responses of desert bighorn sheep to the severe drought observed in 2002. The specific objectives are to investigate: 1) seasonal habitat selection patterns across widely differing climatic periods to determine if desert bighorn use certain habitat features and or behavioral mechanisms to cope with extreme drought; 2) changes in diet selection across climatic periods to determine which forage species are used as buffer resources to maintain populations during droughts; 3) nutritional intake resulting from dietary shifts across climatic periods; and 4) use of vegetation metrics derived from remote sensing data (e.g., NDVI, LAI, EVI) as an index for nutritional quality and abundance of key forage species for desert bighorn sheep. These analyses provide a unique opportunity to assess multiple behavioral responses (e.g., forage selection, habitat selection) of desert bighorn sheep to severe drought through which we hope to identify habitat conditions and key forage species that might buffer desert bighorn populations during future droughts.

We have made significant progress towards objective 2. Primary results are described below. The remaining objectives for the desert bighorn sheep portion of this study will be addressed in FY15. A peer-reviewed publication based on these results will be submitted by 31 January 2015.

Approach: Objective 2.

We sampled 10 forage plots per range per season from 2002 through 2005; plots were sampled during a 4–5 day period during the middle of each season (i.e., February, May, August and November). We used a modified line-intercept method to estimate percent cover of each plant species in the foraging areas using 2 60-m perpendicular line transects intersecting in the center.

We collected ≥ 100 g of 16 forage species which constituted 73-98% ($\bar{x} = 85.4\% \pm 7.9\%$ SD) of the seasonal diets of desert bighorn sheep in the Sierra Pinta and Cabeza Prieta Mountains in

2002–2005 (J.W. Cain, unpublished data). We classified each forage species as grass, forbs, succulent, shrub or tree to assess differences in forage moisture and nutritional content related to plant type.

We dried plant samples at 50° C in a drying oven to a constant weight and determined moisture content. We determined nitrogen (N) content using a TC400 N analyzer and neutral detergent fiber (NDF) and acid detergent fiber (ADF) following the Van Soest method (Van Soest 1994). We analyzed acid detergent lignin (ADL) using the Van Soest ADL assay (Van Soest and Robertson 1980) modified for use with the Ankom fiber bags.

Because we were unable to conduct laboratory analysis for in vitro dry matter digestibility, we used dry matter digestibility (DMD) as calculated by Mould and Robbins (1982) for white-tailed deer (*Odocoileus virginianus*) as:

DMD = (1.06MDS - 18.06) + NDF [(16.39 - 36.95lnX)/100],

where NDS is neutral detergent solubles, 100-NDF(%), and X is lignin and cutin (ADL). Therefore, we used 3 metrics of forage nutritional content in our assessment of the impact of climatic conditions on forage quality and the influence of these metrics on diet selection across widely varying climatic periods: N content, DMD, and moisture content.

Diet Diversity, Breadth, and Forage Selection

We collected 10–20 pellet groups per season per mountain range from female desert bighorn sheep to estimate diet composition using microhistological analysis. Characteristics of the epidermis and cuticle were used to identify plant species. We determined frequency, particle density, and percent composition for each species.

We calculated diet diversity using the Shannon Weiner index (H[^]) and calculated diet breadth using Levins Niche Breadth (B; Levins 1968). To account for individual level variation in diet composition, we calculated these indices for each independent pellet group separately, then summarized this data by season and climatic period.

We estimated sheep forage selection in relation to forage availability using Jacobs' modified electivity D index (Jacobs' D; Jacobs 1974). This is a modification of Ivlev's electivity index E (Ivlev 1961) that is less sensitive to sampling errors for rare species (Lechowicz 1982).

$$D_i = \frac{r_i - p_i}{r_i + p_i - 2r_i p_i}$$

Here D_i is the Jacobs' D index value for forage species *i*, r_i is the proportion of forage species *i* in sheep pellets (i.e., diet), and p_i is the proportion of forage species *i* in the environment (i.e., availability). Jacobs' D values range from -1 to 1, where negative and positive values indicate species avoidance and preference, respectively.

Climatic Periods

We used the Standardized Precipitation Index (SPI; McKee et al. 1993, Guttman 1999) to define the climatic periods during our study. The SPI is the number of standard deviations that observed cumulative precipitation deviates from the long-term average. We defined a drought event as the period when the SPI was consistently negative and reached \leq -1.0 with the drought event beginning when the SPI fell below 0, and ending when the SPI became positive (McKee et al. 1993). We similarly defined wet periods as when the SPI was continuously positive and reached a ≥1.0 and periods near average when the SPI fluctuated near 0, not becoming consistently positive or negative. We used long-term (1969–2005) precipitation data from the weather station nearest our study area (Tacna, Arizona, approx. 64 km north; Western Regional Climate Data Center 2005) to calculate the 3-month SPI for each month from 2002–2005 (Fig. 1). Each sampling period was assigned to 1 of 3 climatic periods based on the 3-month SPI for the month immediately preceding forage sample collection (i.e., SPI was lagged by approximately 2 weeks) and classified as: drought (May, Aug & Nov 2002; Feb2003; Aug 2004), average (May. Aug, & Nov 2003; Feb & May 2004; May & Aug 2005), and wet (Nov 2004, Feb 2005; Fig 1). Our data span a period of exceptional drought (January through October 2002 being the driest period on record), transitioning through a period with near average precipitation and ending during an abnormally wet period (National Oceanic and Atmospheric Administration 2002, 2005).

Statistical Analysis

We used general linear models to assess differences in nutritional quality in relation to climatic period (drought, average, and wet conditions), season (winter, early summer, late summer, and autumn), plant type (succulent, grass, shrub, tree, and forbs), and topographic position. We conducted a separate analysis for N, DMD, and moisture content. Each metric of nutritional quality was entered as the response variable, climatic period, season, and plant type were entered as factors, and topographic position (drainage, slope, and ridgeline) was entered as a blocking factor. We transformed all response variables before analyses using the logit transformation, however estimated marginal means and 95% confidence limits were back transformed for presentation.

We used general linear models to determine changes in diet diversity and diet breadth across seasons and climatic periods. We used the Shannon-Wiener diversity index and Levins' niche breadth as the response variables and season and climatic period were entered as factors.

We assessed the relationships between forage selection (i.e., Jacob's D), nutritional content, and climatic periods using generalized linear models. Jacob's D was entered as the response variable, with N, DMD, and moisture content as continuous predictor variables; climatic period was entered as a categorical predictor variable with the wet period set as the reference level. We then ran models for each plant type independently.

To account for the potentially conflicting limitations in desert bighorn sheep diets (e.g., protein vs. water), we developed an initial set of 21 a priori models (Table 1). Model structures were designed to assess the influence of each forage quality metric individually and in combination with other metrics. We designed some additive models with a common slope but different intercept for each climatic period, and some multiplicative models within interaction terms between forage quality metrics and climatic periods. In addition, to assess the potential for a nonlinear relationship between diet selection and N content, and diet selection and moisture content, we included a quadratic term for these predictor variables.

We employed an information-theoretic approach to assess support for our a priori models using Akaike's Information Criterion (AIC_c) corrected for small sample sizes (Burnham and Anderson 2002). We considered models with Δ AIC_c values <2.0 to be competing models, but models with Δ AIC_c values <7 were considered to have some support. However, when competing models (i.e., Δ AIC_c <2.0) differed from the highest ranking model by the addition of a single predictor variable to the model structure of the highest ranking model, we considered the more complex model to contain an uninformative parameter (Arnold 2010), thus we excluded these models from the AIC_c tables. We calculated model-averaged parameter estimates (± SE) and 90% confidence intervals for variables in highest ranking models using multi-model averaging (Burnham and Anderson 2002) across all a priori models except for those excluded due to uninformative parameters.

We ran pairwise correlations between N, DMD, and moisture content within each plant type to assess the potential for multicollinearity. Nitrogen and moisture content were highly correlated (r > 0.6) for forbs, shrubs and grasses, and DMD and moisture content were correlated (r = 0.69) for succulents; none of the predictor variables were correlated for trees. We therefore never included correlated variables in the same model; however, we retained models with individual correlated variables.

RESULTS

Forage Quality

Mean percent N differed by climatic period ($F_{2, 1103} = 16.63$, P < 0.0001), season ($F_{3, 1103} = 6.367$, P < 0.0001), and plant type ($F_{4, 1103} = 74.38$, P < 0.001). Differences in N content between climatic periods depended on season (climatic period × season interaction; $F_{4, 1103} = 3.34$, P = 0.010). After accounting for plant type, N content did not differ between seasons during the drought period, but was higher during the winter and autumn of the average and wet periods (Fig. 2). Winter N content during the wet period was 25% and 36% higher than during average and drought conditions, respectively (Fig. 2). Winter N content was 52-61% higher during the wet period than during early summer, late summer, and autumn in drought, and 40-46% higher than during periods with average and wet precipitation (Fig. 2). Autumn N content was similar during the use and wet precipitation, but was 19-42% higher during the wet period than during drought in all seasons and 26-29% higher than early and late summer with average precipitation (Fig. 3).

Differences in N content between climatic periods also depended on plant type (climatic period × plant type interaction; $F_{8,1103} = 3.90$, P < 0.0001). After accounting for season, N content of succulents and trees did not differ across climatic periods and N content of grasses and forbs were similar between periods with drought and average conditions (Fig. 3). Nitrogen content was 42-55% higher in grasses and 60-104% higher in forbs during the wet period than when precipitation was average or during drought, but was consistently lower than for shrubs, trees and forbs. Nitrogen content of shrubs increased with increasing precipitation and was 14% higher with average precipitation than during drought and was 30% higher in the wet period than during the period with average rainfall (Fig. 3).

The DMD differed between climatic periods ($F_{2, 1108} = 7.49$, P = 0.001) and plant type ($F_{4, 1108} = 16.25$, P < 0.0001). Differences in DMD between climatic periods depended on season (climatic period × season; $F_{4, 1108} = 3.34$, P = 0.010), plant type (climatic period × plant type; $F_{8, 1108} = 5.54$, P < 0.0001); and season and plant type (climatic period × season × plant type; $F_{16, 1108} = 2.76$, P < 0.0001). The DMD tended to be highest and relatively consistent in succulents, trees and shrubs across all seasons and climatic periods except during the wet period when DMD decreased in grasses (Fig. 4). Grasses had lowest DMD during early and late summer during drought (Fig. 4) and DMD did not differ across climatic periods during winter and autumn for succulents, shrubs, trees, and forbs, but decreased in grasses by 57% during winter in the wet period. Succulent DMD was relatively consistent across seasons and climatic periods with the exception of early summer during drought when it was highest. During the early and late summer, DMD of grasses, shrubs and trees did not differ during drought and average periods.

Plant moisture content differed between climatic periods ($F_{2, 1106} = 38.21$, P < 0.0001), season ($F_{3, 1106} = 4.44$, P = 0.004), and plant type ($F_{4, 1106} = 160.19$, P < 0.0001). Differences in plant

moisture content between climatic periods depended on season (climatic period \times season; $F_{4,1106}$ = 8.55, P<0.0001), plant type (climatic period \times plant type; $F_{8, 1106}$ = 11.50, P<0.0001), and season and plant type (climatic period × season × plant type; $F_{28, 1106} = 3.54$, P<0.0001). During winter, moisture content increased 17% for succulents, 176% for grasses, 45% for shrubs, and 72% for forbs from the average period to the wet period; winter moisture content of trees did not differ between climatic periods (Fig. 5). During early and late summer, only shrubs showed an increase in moisture content, increasing 26% in both seasons during the average period compared with the drought. In autumn, succulent moisture content was 36% higher during the wet period than during drought (Fig. 5). Moisture content of grass during autumn was 256% higher during the average period than during the drought; grass moisture content did not differ between the average and wet periods. Shrub moisture content did not differ during autumn between the average and wet periods however shrub moisture content was 11% higher during the average period and 79% higher during wet period than during the drought. Moisture content of forbs did not differ in autumn between the average and wet periods, but was 104% higher during the average period and 140% higher during the wet period over the drought periods. Moisture content of trees did not differ during autumn between any of the climatic periods (Fig. 5).

Diet Diversity, Breadth, and Forage Selection

Differences in diet diversity and diet breadth across seasons depended on climatic period (H': climatic period × season; $F_{4, 349} = 23.55$, P < 0.0001; B: climatic period × season; $F_{4, 349} = 223.12$, P < 0.0001). Both diet diversity and diet breadth followed similar seasonal patterns across climatic periods with a contraction in diversity and breadth during the drought period. Mean diversity was lowest during winter and early summer of the drought period and diet breadth was smallest across all seasons of the drought period with the exception of autumn. The average precipitation period generally had intermediate levels of diversity and diet breadth, increasing during the wet period.

The most supported model (Akaike weight $w_i = 0.543$) for the selection of forbs included DMD with a common slope but separate intercepts for climatic periods (Table 2). Contrary to our expectation, selection of forbs was negatively associated with DMD, the intercept was lowest for the drought, intermediate for average period and highest during for the wet period.

For the selection of grasses, the highest ranking model ($w_i = 0.647$) included N content with a common slope but separate intercepts for climatic periods (Table 2). Selection of grasses was negatively associated with N content. The intercept was highest for the wet period, intermediate for drought and lowest for the normal period.

The highest ranking ($w_i = 0.385$) model for the selection of shrubs included N content, the quadratic term for N content, and a common slope but separate intercepts for climatic periods (Table 2). Selection of shrubs was associated with N content in a quadratic fashion, with selection peaking at intermediate levels of N content. Selection was highest for shrubs at intermediate N levels for the wet period, lower for normal rainfall, and lowest for drought (Table 3).

Selection of succulents by desert bighorn sheep was best described by the model which included DMD with common slope but separate intercepts for climatic periods ($w_i = 0.675$; Table 2). Selection of succulents declined with increasing DMD and moisture content (Table 3).The intercept was highest for the wet period, lowest for drought and intermediate for normal period.

The most supported model for the selection of tree species included N and moisture content, with common slope but separate intercepts for climatic periods ($w_i = 0.562$; Table 2). Selection

of trees was positively associated with N content and moisture (Table 3). The intercept was highest for the wet period, lowest for drought and intermediate for normal period.

Table 1. A priori models for predicting forage selection by desert bighorn sheep as a function of nutritional quality metrics and rainfall conditions.

Model no.	Model Structure ^a				
1	Null (intercept only)				
2	N + Climate				
3	$N + N^2 + Climate$				
4	Moist + Climate				
5	$Moist + Moist^2 + Climate$				
6	$N + Moist + Moist^2 + Climate$				
7	$N + N^2 + Moist + Climate$				
8	N + Moist + Climate				
9	$N + N^2 + Moist + Moist^2 + Climate$				
10	DMD + Climate				
11	DMD + N + Climate				
12	DMD + Moist + Climate				
13	DMD + N + Moist + Climate				
14	$DMD + N + N^2 + Climate$				
15	$DMD + Moist + Moist^2 + Climate$				
16	$DMD + N + N^2 + Moist + Moist^2 + Climate$				
17	$N + Climate + N \times Climate$				
18	Moist + Climate + Moist x Climate				
19	$DMD + N + Climate + N \times Climate + DMD \times Climate$				
20	$DMD + Moist + Climate + Moist \times Climate + DMD \times Climate$				
21	$DMD + N + Moist + Climate + N \times Climate + DMD \times Climate + Moist \times Climate$				
^a Variable notation: N – forage nitrogen content Climate – climatic period (drought normal					

^a Variable notation: N = forage nitrogen content, Climate = climatic period (drought, normal, wet), Moist = forage moisture content, DMD = dry matter digestibility as calculated by Mould and Robbins (1982).

Model	K	AIC _c	ΔAIC_{c}	Wi
Forbs				
DMD + Climate	4	56.33	0.0	0.543
Null	1	58.05	1.72	0.229
DMD + Moist + Climate	5	59.62	3.29	0.105
$DMD + N + N^2 + Climate$	6	61.42	5.09	0.043
Moist + Climate	4	62.85	6.52	0.021
Grass				
N + Climate	4	49.22	0.0	0.647
DMD + N + Climate	5	52.60	3.38	0.119
N + Climate + N \times Climate	6	53.75	4.53	0.067
$Moist + Moist^2 + Climate$	5	53.84	4.62	0.064
Null	1	54.49	5.27	0.046
Shrubs				
$N + N^2 + Climate$	5	106.74	0.0	0.385
$DMD + Moist + Moist^2 + Climate$	6	107.76	1.02	0.231
$Moist + Moist^2 + Climate$	5	109.19	2.45	0.113
$N + Climate + N \times Climate$	6	110.13	3.39	0.071
DMD + N + Climate	5	110.99	4.24	0.046
Succulents				
DMD + Climate	4	78.43	0.0	0.675
DMD + N + Climate	5	80.84	2.41	0.202
$DMD + N + N^2 + Climate$	6	81.98	3.55	0.114
Moist + Climate	4	88.99	10.56	0.003
$Moist + Moist^2 + Climate$	5	90.82	12.39	0.001
Trees				
N + Moist + Climate	5	58.41	0.0	0.562
DMD + N + Climate	5	62.22	3.82	0.083
$DMD + N + N^2 + Moist + Moist^2 + Climate$	8	62.53	4.12	0.072
$N + N^2 + Moist + Moist^2 + Climate$	7	62.59	4.19	0.069
N + Climate	4	62.89	4.49	0.060

Table 2. Five highest ranking a priori models assessing the relationship between forage selection by desert bighorn sheep, nutritional quality and climatic period.

Table 3. Model-averaged logistic regression coefficient estimates, standard errors, and 95% confidence limits for variables in the best approximating models for the relationship between forage selection by desert bighorn sheep and forage nutritional content and climatic period.

Variable	Model-averaged para	ameter estimate.	90% Confidence limits			
	Estimate	SE	Lower CL	Upper CL		
	Forbs					
Ν	229.79	527.78	-637.86	1097.44		
Climate (drought)	-0.49	0.59	-1.46	0.48		
Climate (average)	-0.27	0.57	-1.20	0.66		
DMD	-4.99	1.71	-7.79	-2.18		
Moisture	0.01	2.42	-3.79	4.00		
		Grass				
Ν	-175.68	53.93	-264.40	-86.97		
Climate (drought)	-0.66	0.46	-1.42	0.09		
Climate (average)	-0.89	0.41	-1.56	-0.22		
DMD	-0.47	0.92	-1.97	1.04		
Moisture	6.40	3.03	1.41	11.39		
		Shru	bs			
N	70.50	43.50	-1.06	142.06		
N^2	-4368.64	1656.83	-7093.96	-1643.32		
Climate (drought)	-0.41	0.21	-0.75	-0.07		
Climate (average)	-0.29	0.19	-0.61	0.02		
DMD	-1.33	0.74	-2.55	-0.12		
Moisture	4.99	1.75	2.10	7.87		
	Succulents					
Ν	-112.86	112.67	-298.19	72.47		
Climate (drought)	0.26	0.28	-0.20	0.71		
Climate (average)	0.28	0.27	-0.17	0.73		
DMD	-5.69	0.69	-6.83	-4.55		
Moisture	-3.52	1.86	-6.58	-0.46		
	Trees					
Ν	68.48	40.77	1.41	135.55		
Climate (drought)	-0.12	0.27	-0.56	0.32		
Climate (normal)	-0.07	0.26	-0.49	0.35		
DMD	1.35	1.19	-0.60	3.31		
Moisture	8.95	4.48	1.58	16.33		

Figure 1. Standardized precipitation index calculated from long-term (1969-2005) precipitation data from Tacna, Arizona, January 2002 – September 2005.



Figure 2. Mean seasonal nitrogen content of desert bighorn sheep forage during climatic periods with drought (closed black symbols), average (open symbols) and wet (closed gray symbols) rainfall conditions. Circles are winter (Jan – Mar), triangles are early summer (Apr – Jun), squares are late summer (Jul – Sep), and diamonds are autumn (Oct – Dec). Means and error bars are back-transformed estimated marginal means and 95% confidence intervals.



Figure 3. Mean nitrogen content of desert bighorn sheep forage by plant type for climatic periods with drought (closed black symbols), average (open symbols) and wet (closed gray symbols) rainfall conditions. Circles are succulents, downward pointing triangles are grasses, squares are shrubs, diamonds are trees, and upward pointing triangles are forbs. Means and error bars are back-transformed estimated marginal means and 95% confidence intervals.







Figure 4. Mean seasonal dry matter digestibility (DMD) content of desert bighorn sheep forage by plant type during climatic periods with drought (black error bars with closed symbols), average (black error bars with open symbols) and wet (gray error bars with closed symbols) rainfall conditions. Circles are winter (Jan – Mar), downward pointing triangles are early summer (Apr – Jun), squares are late summer (Jul – Sep), and diamonds are autumn (Oct – Dec). Means and error bars are backtransformed estimated marginal means and 95% confidence intervals.



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Impact of Drought on Southwestern Pronghorn Population Trends and Predicted

Trajectories in the Southwest in the Face of Climate Change

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Problem statement and implications: Many pronghorn populations across the Southwest appear to be declining. In response, managers are applying various techniques in attempts to increase pronghorn numbers often without a clear understanding of the causes of these declines. Some population declines have been associated with drought conditions resulting in reduced forage quality and quantity impacting survival of adults and fawns. Various climate change models predict warmer and drier conditions, which is likely to exacerbate future drought-related population declines, forcing managers to make some difficult decisions regarding the long-term viability of their management practices and the persistence of some pronghorn populations in the Southwest. In collaboration with the USFWS, we will undertake a meta-analysis of pronghorn population trends in the Southwest in relation to climatic conditions, specifically drought.

Goals and objectives: In this study we aim to: 1) determine the extent of pronghorn decline in the Southwest; 2) identify climatic factors which best predict these declines; and 3) use global climate forecast data to project how climate change may effect pronghorn population dynamics to the end the of the century. Quantifying the relationship between climatic conditions and pronghorn population trajectories is central to developing appropriate management actions for pronghorn in the face of climate change. The development of pronghorn management strategies spanning multiple populations and differing habitat conditions have mostly used inferences from studies of single populations; however, evidence suggests that there can be significant variation among local pronghorn populations in factors explaining density and recruitment (Hoffman et al. 2010).

We adopt an information-theoretic approach in a Bayesian framework to analyze long-term data from pronghorn populations in Utah, Arizona, New Mexico, and Texas, to determine climatic factors that predict annual rate of population change (λ). We then use these predictors to project long-term pronghorn population trends in response to predicted changes in climate. However, populations do not simply respond to approximated global averages, but rather regional changes, which are highly spatially heterogeneous, and are more relevant in the context of ecological response to climatic change (Walther et al. 2002). Therefore, we employ climate data derived from region-specific downscaled climate projection models to predict future pronghorn population dynamics.

This project will contribute to the development of conservation and management plans for pronghorn populations across the southwestern U.S. This will enable wildlife managers responsible for managing these pronghorn populations to make scientificallyinformed decisions when developing management strategies.

Approach

We are analyzing long-term pronghorn population data from annual aerial surveys conducted in Utah, Arizona, New Mexico, and Texas. Within each state, we define subpopulations based on physical barriers (e.g., rivers, canyons, mountain ranges, major highways, etc.), variation in precipitation patterns, and availability of population data. We calculate annual rate of population change (λ) as our response variable. This is a useful metric

for evaluating population performance because it summarizes survival and recruitment rates and can be used for open populations (Nichols and Hines 2002). When population-specific harvest and translocation data are available, population estimates for calculating λ are adjusted according to the following equation:

$$\lambda_t = \frac{N_t}{N_{t-1} - h - r + a} \tag{1}$$

where λ_t is population change from time *t*-1 to *t*, N_t and N_{t-1} are population estimates from current and previous surveys, respectively, *h* is number of pronghorn harvested, and *r* and *a* are number of individuals removed from and released into the population, respectively, through translocations. Although survey methods and periods may vary among states and/or populations, constant pronghorn detectability is assumed.

Climate data (precipitation [mm/day] and mean temperature [°C]) are derived from historical and future simulations from the World Climate Research Programme's Coupled Model Intercomparison Project phase 5 (CMIP5) Global Climate Models (GCM) subset from the National Center for Atmospheric Research Community Climate System Model version 4 (CCSM4). Comparisons of GCM historical simulation results with observations often show biases, which may vary by location and/or season. A monthly bias-correction and spatial disaggregation (BCSD) statistical downscaling technique is used to correct for such biases (Wood et al. 2004; Maurer 2007). Model evaluations demonstrated that results from downscaling algorithms were in good agreement with observations, with precipitation and average surface temperature biases of ± 0.04 mm/day and $\pm 0.05^{\circ}$ C, respectively, for all values for all time steps and grid cells (Brekke et al. 2013). These climate data have a 1/8 degree grid resolution, and thus, for monthly precipitation and temperature calculations, we take the mean of grids across pronghorn range falling within population boundaries.

Our aim is to compare two realistic future global climate situations; a more optimistic lower atmospheric C0₂ concentration scenario (ACCS) and a more pessimistic high ACCS. Therefore, our climate projections were modelled from data derived from the BCSD CMIP5 Representative Concentrations Pathways (RCP) 4.5 and 8.5 (Moss et al. 2010; van Vuuren et al. 2011). These scenarios attempt to account for external factors that have affected climate in the past, since GCMs calculate their own internal patterns of natural variability. External factors include the forcing of greenhouse gases, aerosols, and reactive species from anthropogenic emissions, changes in solar output, particulate emissions from volcanic eruptions, and changes in tropospheric and stratospheric ozone (Hayhoe and Stoner 2014). The RCP8.5 pathway represents a comparatively high ACCS of continued global dependency on fossil fuels, whereby atmospheric C0₂ concentrations approach 2.5 times current levels by 2100 (Riahi et al. 2011). The RCP4.5 pathway represents a lower ACCS, whereby there is an increase of about 60% in atmospheric C0₂ concentrations by mid-century, followed by a decline to near 1990 levels by 2100 (Thomson et al. 2011).

In addition to testing mean temperature and total precipitation as predictors of pronghorn population dynamics, we also test the drought index Standardized Precipitation Index (SPI; McKee et al. 1993; Guttman1999), which is the number of standard deviations that observed cumulative precipitation deviates from the long-term climatological average. We calculate SPI for 3-, 6-, 12-, and 24-month periods from all available monthly precipitation data in the BCSD CMIP5 climate dataset using program SPI SL 6 (National Drought Mitigation Center 2014).

For our explanatory variables, we summarize monthly mean temperature, total precipitation, and mean SPI (3-, 6-, and 12-month periods) by important phases in an adult female's annual reproductive cycle relative to peak fawning (early, mid-, and late gestation

and lactation). Peak pronghorn fawning is usually over three weeks during the early growing season, with the majority of births occurring within a ten day period (Autenrieth and Fichter 1975). In our study area, fawning peaks in mid-April in southern Arizona, in mid-May in northern Arizona and Texas Trans-Pecos, and in late May in Utah, New Mexico, and Texas Panhandle (Buechner 1950; Larsen 1964; Canon 1993; Ticer et al. 2000; Miller & Drake 2006; J. Weaver pers. comm., A. Aoude pers. comm.). We also summarize mean temperature, total precipitation, and mean SPI for 12- and 24-month periods preceding each population survey. All data are scaled prior to analysis by subtracting the mean and dividing by standard deviation (Gelman and Hill 2007).

We use Bayesian inference to estimate parameters from regressions using a Markov-Chain Monte Carlo (MCMC) technique by creating models in R 3.0.2 (R Core Team 2013) and running them in OpenBUGS 3.2.3 (Lunn et al. 2009) using R2OpenBUGS (Sturtz et al. 2005). We model λ as a log-linear function with an uninformative N(0,100) prior assigned to regression coefficients and G(0.001, 0.001) assigned to hyperparameters. Model convergence is assessed in OpenBUGS using the Brooks-Gelman-Rubin diagnostic tool (Gelman and Rubin 1992; Brooks and Gelman 1998) after simultaneously running two Markov chains with different initial values. For each model, we run 20,000 MCMC iterations, discarding the initial 10,000 MCMC samples as burn-in. We use an information-theoretic approach whereby competing models are ranked by their deviance information criterion (DIC, Spiegalhalter et al. 2002). DIC measures the fit of the model to the data, with a penalty for model complexity, and models within two DIC units of the most parsimonious model (i.e., the model with the lowest DIC value) are considered to have to have higher predictive value (Spiegalhalter et al. 2002; Burnham and Anderson 2002).

For each population, we determine which climate metrics best predict λ by first running separate models with a single precipitation or a single temperature covariate (plus a covariate for density effect). We run separate model comparison sets for precipitation and temperature. We then test precipitation and temperature covariates from the best-fit models together in individual models, as well as those models with an added term for the interaction between precipitation and temperature (Eqn. 2).

$$\ln(\lambda_t) = \beta_0 + \beta_1 X_{N[t-1]} + \beta_2 X_{prec} + \beta_3 X_{temp} + \beta_4 X_{prec*temp}$$
(2)

We run the top combined model with precipitation and temperature data derived from the BCSD CMIP5 RCP4.5 and RCP8.5 datasets to predict λ_t . If the Δ DIC of the top single climate covariate model is ≥ 10 (i.e., no support for the data), λ_t is predicted from only precipitation or only temperature data. We use λ_t to project annual pronghorn population size and probability of extirpation to the year 2090 using an integrated modeling approach (Schaub and Abadi 2011) whereby we generate population projections concurrently with estimates of λ_t , such that estimation of uncertainty is propagated into the projections. Population projection models are created in R 3.0.2 (R Core Team 2013) and run in JAGS 3.4.0 (Plummer 2003) using R2jags (Su and Yajima 2010). Population projections are made in the absence of any management intervention (harvest or translocation) and assume that pronghorn peak fawning periods will not significantly shift as a result of climate change. For populations projected to fail, we will test whether there is potential for population recovery through translocations. We will do so by incorporating a management scenario where the population is supplemented with a fixed number of pronghorn annually or biennially, to determine the level of supplementation required for the population to persist, while ensuring the source population can sustain these removals.

Progress To Date

- Compiled from state agencies all available population, harvest, and translocation data for Arizona, New Mexico, and Texas (Table 1). Data for Utah is currently incomplete.
- Defined 16 populations with sufficient data for modelling (Table 1) Arizona 5; New Mexico 5; Texas 2; Utah 4 (not confirmed).
- Reviewed available GCMs and selected data from the latest GCM (BCSD CMIP5) which utilizes a more advanced statistical downscaling technique and has particular applicability to the southwest U.S.
- Downloaded all climate data and for one population data has been prepared for analysis.
- Developed models in R for execution in OpenBUGS to predict climatic factors that influence pronghorn population growth.
- Developed integrated population projection model in R for execution in JAGS.
- Completed modelling of one population Texas Trans-Pecos (Fig. 1).

Results

Texas Trans-Pecos Population

- The model that best predicted λ included total precipitation during lactation, mean temperature in the 2 years prior to population surveys, and the interaction of these covariates (Table 1).
- Based on median population projections, under the lower (RCP4.5) and high (RCP8.5) ACCS and without management intervention, the population is predicted to be extirpated by the mid-2040s and mid-2030s, respectively (Fig. 1).
- Based on the lower 2.5% credible intervals, the population is at risk of disappearing in the next 10 years under the high ACCS and 15 years under the lower ACCS (Fig. 1).
- The upper 97.5% credible intervals predict that in the best case scenario, the population may persist into the early 2070s under the high ACCS, whereas under the lower ACCS, it would be approaching extirpation by 2090 (Fig. 1). However, these intervals are wide, and thus there is high uncertainty in these projections.
- Under the lower ACCS, the probability of extirpation of this population surpasses 50% in 2046 and reaches 96% by 2090. Under the high ACCS, probability of extirpation is 50% in 2036 and increases to 98% by 2090.

0	Survey	n	Population	Area		Reproducti	ve Periods ^b		
Population	Period ^a	(years)	Range	(km^2)	Lactation	Early Gestation	Mid-gestation	Late Gestation	Regression equations for projections ^c
Utah									
Northwest (NW)					Jun-Sep	Sep-Nov	Dec-Feb	Mar-May	
West (W)					Jun-Sep	Sep-Nov	Dec-Feb	Mar-May	
East (E)					Jun-Sep	Sep-Nov	Dec-Feb	Mar-May	
South (S)					Jun-Sep	Sep-Nov	Dec-Feb	Mar-May	
Arizona									
Northwest (NW)	1975-2013	39	48-619		May-Aug	Sep-Nov	Dec-Feb	Mar-May	
Central (C)	1961-2013	53	1,663-5,802		May-Aug	Sep-Nov	Dec-Feb	Mar-May	
East-Central (EC)	1961-2013	53	391-2,808		May-Aug	Sep-Nov	Dec-Feb	Mar-May	
Southeast - N10 (SEN10)	1961-2013	52	29-341		Apr-Jul	Aug-Oct	Nov-Jan	Feb-Apr	
Southeast - S10 (SES10)	1961-2013	52	11-420		Apr-Jul	Aug-Oct	Nov-Jan	Feb-Apr	
New Mexico									
Northeast (NE)	1984-2008	19	1,327-2,828		Jun-Sep	Sep-Nov	Dec-Feb	Mar-May	
East (E)	1992-2009	15	71-239		Jun-Sep	Sep-Nov	Dec-Feb	Mar-May	
East-Central (EC)	1978-2009	20	162-474		Jun-Sep	Sep-Nov	Dec-Feb	Mar-May	
Central (C)	1991-2011	15	210-576		Jun-Sep	Sep-Nov	Dec-Feb	Mar-May	
Southwest (SW)	1992-2011	17	86-240		Jun-Sep	Sep-Nov	Dec-Feb	Mar-May	
Texas									
Trans-Pecos (TP)	1978-2012	35	2,751-17,226		May-Aug	Sep-Nov	Dec-Feb	Mar-May	$\ln(\lambda_t) = 0.02 - 0.14X_{N[t-1]} + 3.0X_{PrecLac} + 0.16X_{TempAnn24} - 1.62X_{PrecLac*TempAnn24}$
Panhandle (PH)	1978-2012	35	2,568-12,968		Jun-Sep	Sep-Nov	Dec-Feb	Mar-May	

Table 1. Pronghorn populations modelled in the Southwest USA.

^a Population surveys conducted July/August in Arizona and Texas, April in New Mexico, and March/April in Utah.

^b Sources for peak fawning periods - Buechner 1950; Larsen 1964; Canon 1993; Ticer et al. 2000; Miller and Drake 2006; J. Weaver pers. comm.; A. Aoude pers. comm.

^c Covariates used in population projection models: PrecLac = total precipitation during lactation; TempAnn24 = mean temperature over 24 months prior to population survey; N[t-1] = population estimate in previous year (density effect).

Figure 1. Pronghorn population projection from an integrated Bayesian model for Texas Trans-Pecos under a high (RCP8.5, black) and a lower (RCP4.5, gray) emissions scenario from 2014 to 2090 based on an estimated initial population size of 3,016 in 2013. Solid line represents estimated median population and dashed lines represent 2.5% and 97.5% credible intervals. Dotted line represents annual population estimates from aerial surveys (1977-2013).



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Drought Effects on Habitat and Stream Connectivity of Rio Grande Cutthroat Trout Conservation Populations

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Problem statement and implications: Rio Grande cutthroat trout (RGCT), the southernmost subspecies of cutthroat trout, is endemic to the Rio Grande, Canadian, and Pecos River basins of Colorado and New Mexico. The subspecies is currently restricted to approximately 12% of its historic range with most populations occupying isolated high elevation headwater streams (Alves et al. 2008). A recent status review found that listing of the subspecies under the Endangered Species Act of 1973 was warranted, but precluded by higher priority actions (U.S. Federal Register 2008). The status review listed climate change as a major threat to the subspecies future persistence. Although the majority of studies examining the negative effects of climate change on salmonid species have focused on changes in stream temperatures, future decreases in precipitation are expected to profoundly affect RGCT because the majority of populations occupy streams that are small (Zeigler et al. 2013) and highly fragmented (Alves et al. 2008).

An ongoing monitoring program of stream temperature and summer baseflow of RGCT populations was initiated in 2010. Although the majority of RGCT populations occupy thermally stable habitat, a large portion of these populations occupy small streams with extremely low summer baseflow (< 1.0 cubic foot per second, cfs; Zeigler et al. 2013). Since 2010, low winter snowpack and reduced seasonal precipitation across the subspecies' range have resulted in baseflows well below 1.0 cfs, with extended reaches of streams becoming dry (Zeigler and Todd, unpublished data). As a result of this suspected widespread stream intermittency, additional funds were obtained in 2012 to develop and deploy stream temperature/flow intermittency loggers within populations of RGCT experiencing extremely low summer baseflows (< 0.50 cfs). Although these new sensors are documenting critical information regarding the extent and duration of stream intermittency, we do not know the effects that intermittency has had on the demographics (growth, recruitment, health) of RGCT populations. The full extent of how drought will impact RGCT is unknown because only a portion of the 120 RGCT populations are monitored annually by State and Federal management agencies. The current drought (2011-2013) within the Rio Grande basin provides a unique opportunity to study the impacts of extended drought on a sensitive coldwater fish species with high ecosystem importance and management relevance.

Interim Results of 2014 Reporting Period: Stream Temperature Intermittency and Conductivity loggers (STICs) and ProV2 temperature loggers were deployed May 2013 throughout 30 RGCT populations and were retrieved September 2014 (Table). Rio Grande cutthroat trout populations were selected based on stream size, baseflows <0.5 cfs, and previous evidence of intermittency. Of note, stream intermittency was not observed at the time the STICs were retrieved throughout RGCT populations; thus, habitat surveys to characterize the effects of intermittency on pools (size and number) were not conducted. Analysis of intermittency and flow duration as well as stream temperature is underway.

During the reporting period, USFWS published the decision that RGCT is not warranted for listing as an endangered or threatened species under the 1973 Endangered Species Act (USFWS)

2014). The species was not in danger of extinction throughout its range nor was it likely to become extinct in the foreseeable future.

Stream Name	Population ID	Basin	Number of STICs
McCrystal Creek	11080002cp001	Cimarron	3
Middle Ponil Creek	11080002cp003	Cimarron	1
E. F. Luna Creek	11080004cp001	Mora	2
Cat Creek	13010002cp002	Alamosa-Trinchera	3
Jim Creek	13010002cp005	Alamosa-Trinchera	1
Torsido Creek	13010002cp009	Alamosa-Trinchera	1
Torcido Creek	13010002cp010	Alamosa-Trinchera	1
Deep Creek	13010002cp012	Alamosa-Trinchera	1
West Indian Creek	13010002cp015	Alamosa-Trinchera	1
Wagon Creek	13010002cp016	Alamosa-Trinchera	1
Sangre de Cristo Creek	13010002cp016	Alamosa-Trinchera	5
East Pass Creek	13010004cp002	Saguache	1
Jacks Creek	13010004cp003	Saguache	1
Cross Creek	13010004cp003	Saguache	1
M. F. Carnero Creek	13010004cp007	Saguache	4
N. F. Carnero Creek	13010004cp008	Saguache	4
Prong Creek	13010004cp011	Saguache	1
Cave Creek	13010004cp012	Saguache	1
Tio Grande	13010005cp002	Conejos	1
Tanques Creek	13010005cp003	Conejos	1
Rio Nutrias	13010005cp004	Conejos	2
Powderhouse Creek	13020101cp004	Upper Rio Grande	3
La Queva Creek	13020101cp005	Upper Rio Grande	1
Grassy Creek	13020101cp006	Upper Rio Grande	1
Comanche Creek	13020101cp006	Upper Rio Grande	2
Vidal Creek	13020101cp006	Upper Rio Grande	1
Rito de las Palomas	13020202cp002	Jemez	3
Rito de los Pinos	13020204cp002	Rio Puerco	1
Osha Canyon	13020101cp024	Upper Rio Grande	3
Pinelodge Creek	13060005cp001	Arroyo del Macho	2

Table 1. Streams throughout New Mexico and Colorado with populations of Rio Grandecutthroat trout streams where Stream Temperature, Intermittency and Conductivitylogger (STICs) were deployed August 2013 and retrieved September 2014

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Effects of Climate on Scaled Quail Reproduction and Survival

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Problem statement and implications: Across the southwestern U.S., long-term declines in populations of scaled quail and contraction of their range-wide distribution have caught the attention of avian ecologists (Cantu et al. 2006). One of the factors hypothesized as a primary cause of this decline is a long-term trend in warmer, drier conditions and reduced monsoonal rainfall across their range. The mechanism believed to be driving this trend is declining nest success due to temperature and humidity levels above a critical threshold for egg and chick survival. While habitat loss cannot be discounted as a possible driver, areas managed specifically for scaled quail in western Texas have seen similar losses in population numbers across the same time frame indicating that these reductions are independent of habitat related factors (Rollins 2000). Coupled with climate models forecasting shifts in the arrival of summer monsoon rains away from the critical reproductive periods of June and July (Cook and Seager 2013), the longterm forecast for scaled quail response to decreased rainfall and higher temperatures is bleak. Scaled quail are considered to be a key indicator species of the health of the habitats they occupy across the southwest and are frequently used to assess the success of restoration projects undertaken by federal and state agencies (Coffman 2012). We propose to use this species to study climate effects (temperature, humidity, and precipitation) preceding, during and following the nesting season with a primary focus on how these climate variables affect nest success.

Goals and Objectives: Our primary objective will be to measure nest success in different populations across their range and determine if nest success is related to temperature and humidity measurements taken in incubating nests using ibuttons. This project could be expanded in future years if funding becomes available to compare presence/absence of scaled quail on White Sands Missile Range (where habitat condition is driven by only climate variables because grazing has not occurred in over 50 years) using drought indices to determine if measures of precipitation, temperature and humidity can predict scaled quail abundance.

Project activities during reporting period and current status: For the 2014 breeding season we deployed temperature and humidity loggers in scaled quail nests in New Mexico, Texas, and Oklahoma. We have not received the logger data from Texas and Oklahoma, but we have added two new sites. We will be starting an additional project on White Sands Missile Range and placing data loggers in scaled quail nests in Arizona in 2015. We have collected and analyzed the data from nests here in New Mexico from the 2014 nesting season and will be deploying data loggers at all sites across the range again in 2015.

2014 Results

Precipitation patterns during the growing season in 2014 were characterized by initial precipitation beginning in early July and increasing in frequency and magnitude through the beginning of October (Figure 1). High rainfall in October was the result of a tropical storm followed by a hurricane on the northwest coast of Mexico and is atypical of the end of the monsoon season. Nests were first initiated in June before the onset of summer monsoon rains and continued through late September; the end of the monsoon season. Temperature and humidity data from inside and immediately outside the nest indicate that scaled quail hens were very good at buffering nest temperatures from ambient temperatures, but poor at buffering nests from both

small and large changes in ambient humidity (Figure 2). Interestingly, nest success seemed unaffected by ambient temperature and humidity with nest success being highest prior to the onset of summer monsoons when ambient temperature is highest and humidity lowest (Figure 3A and Figure 2, respectively). One of the biggest drivers of overall reproductive success in 2014 appeared to be onset of summer monsoons. Brood success increased as the monsoon season progressed with 100% brood survival observed in September and October (Figure 3B).



Figure 1. Total weekly precipitation at our New Mexico study site during the 2014 monsoon season.



Figure 2. Scaled Quail hens appear to buffer the temperature of the nest across both hot and cool periods (A), but appear to buffer ambient humidity poorly (B). Black lines depict nest temperature and humidity; gray lines represent ambient conditions



Figure 3. Scaled quail nest success (A) varied widely while brood success (B) increased through the breeding season indicating that brood success is more dependent on summer monsoons than nest success.

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